Route Optimization for Energy Efficient Airport Shuttle Operations – A Case Study from Dallas Fort Worth International Airport

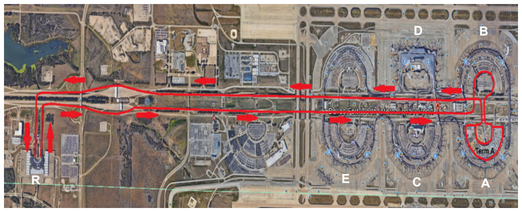
Devon Sigler[1], Qichao Wang[1] , Zhaocai Liu[1] , Venu Garikapati[1], Andrew Kotz[1], Kenneth J Kelly[1], Monte Lunacek[1], Caleb Phillips[1]

[1] National Renewable Energy Laboratory (NREL)

OVERVIEW

❑ ***Context***

- Dallas Fort Worth International Airport (DFW) operates approximately 200 shuttle buses across various service operations. 55 of those serve the rental car center moving passengers between terminals A,B,C,D,E and a rental car center (R).
- The rental car shuttle fleet consumes 693,817 gasoline gallons equivalent (GGE) of fuel per year and generates 5,700 tons of CO_2 each year.



❑ ***Goals***

- Use optimization modeling combined with discrete event simulation to solve the 'travel within the airport premises' shuttle route optimization problem with respect to the DFW rental car center.
- Explore tradeoffs between passenger wait times and the energy efficiency of transporting passengers between the rental car center and the terminals at DFW.

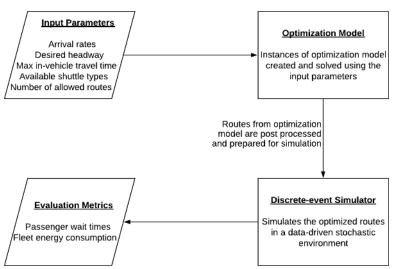
METHODOLOGY

❑ ***Optimization Model***

- Mixed Integer Linear Program (MILP)
- Solves the dispatching problem to minimize hourly energy consumption by the bus fleet
- Provides a set of shuttle routes
- Assigns a bus size for each route
- Determines the number of buses serving each route

❑ ***Discrete-event Simulator***

- Tests the performance of the routing solution provided by the optimization model in a stochastic environment
- Uses stochastic dwell times, travel times, and arrival rates.



DATA

❑ ***Controller Area Network (CAN) Bus Data***

- DFW allowed NREL researchers to collect CAN bus data from the airport rental car shuttles using vehicle data loggers resulting in approximately 100,000 miles of 1Hz data from 14 buses over a period of one month of shuttle operations.

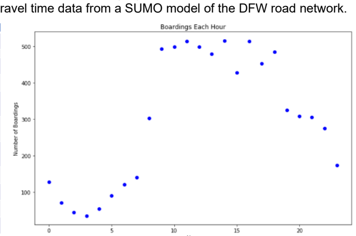
❑ ***Spatial Positioning on Transit (SPOT) Data***

- DFW allowed NREL access to their SPOT database. SPOT data uses commercial hardware to capture information pertaining to shuttle operations. Some noteworthy functionalities of SPOT data are: i) providing boarding and alighting data; ii) calculating bus arrival predictions and assessing on-time performance of the shuttles; iii) managing vehicle headways and viewing shuttle schedules.

❑ ***Data Used for the Optimization Model and the Discrete-event Simulator***

- SPOT data combined with CAN data provided the information required to estimate various model parameters and construct empirical distributions for simulation purposes.
- Travel time data was supplemented with travel time data from a SUMO model of the DFW road network.

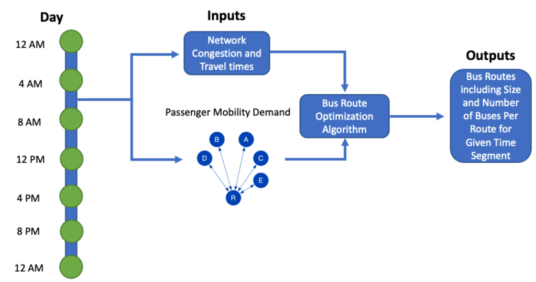
	Aircraft Hardstand	Employee	Remote	Rental Car
Vehicles Logged	4	12	4	14
Miles Logged	676	103,987	20,821	99,840
Active Days Logged	100	412	89	544
Avg. Moving Speed [mph]	12.9	18.7	21.4	20.6
Avg. Daily Distance [miles]	6.8	252.4	233.9	183.5
Max Daily Distance [miles]	20.7	384.9	367.2	306.5
Avg.Fuel Economy [MPG_{DE}]	n/a	4.1	4.1	4.3
Avg. Daily Run Time [hrs]	n/a	19.5	8.2	14.4
Avg. Daily % Idle	n/a	31.8%	46.4%	38.9%
Flywheel Energy [kWh]	n/a	641.1	271.4	379.4
Avg. Daily % Energy at Idle	n/a	16.2%	19.7%	14.9%



ROUTE OPTIMIZATION

❑ ***Optimization of Routes***

- For a specified day of week and time of day data is collected that characterizes passenger mobility demand and road network travel times.
- Passenger experience parameters are specified by user, namely max in-vehicle travel time (ivtt) and bus headways (hw).
- A MILP model instance is then constructed and solved.



❑ ***Strengths***

- **Data Driven:** Uses CAN bus data, SPOT bus data, and simulated data from a SUMO model of the road network to inform the calculation of optimal routes.
- **Customer Oriented**: The selection of routes can consider passenger experience constraints, namely bus headway and max in-vehicle travel time for passengers along the route.
- **Time Adaptive**: Routes can be computed for specific time windows throughout the day, and specific days of the week.
- **Fleet Oriented:** Different bus types and sizes can be considered for each route.

❑ ***Limitations***

- **Averages:** Uses average travel times, passenger arrival rates, and dwell times, which do not capture the variance that occurs between different loops performed by the buses.
- **Perfect Spacing:** Assumes perfect spacing of the buses along a route which unlikely to be achieved in practice.

DISCRETE EVENT SIMULATION

❑ ***Airport Shuttle Planning and Improved Routing Event-Driven Simulation (ASPIRES):***

- To test the performance of the solutions generated by the optimization model an open-source event-driven simulator, ASPIRES, was developed.
- ASPIRES was developed as a Python module to simulate and evaluate the current as well as optimized airport shuttle operations.
- ASPIRES takes the output of the optimization model and simulates airport shuttle operations using empirical probability distributions of travel times, dwell times, and passenger arrivals.
- The ASPIRES module addresses calibration issues faced by most traffic simulation packages by carrying out event-driven simulations based on empirical distributions of real-world data.
- ASPIRES is highly optimized and can simulate a day of airport shuttle operations in a second.

COMPUTATIONAL EXPERIMENTS

❑ ***Large Scale Optimization Model Runs***

- To explore the tradeoff between energy efficiency and passenger travel experience (i.e., passenger wait times), shuttle route optimization runs for all permutations of the parameters in the table were carried out on NREL HPC system Eagle, leading to a total of 2,268 model runs.

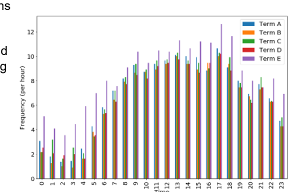
Parameter	Values
Day of the Week	M, T, W, Th, F, Sa, Su
Time of Day	12am-8am,8am-7pm, 7pm-12am
Arrivals Standard Deviation	0,1,2
Max Ride Length	15,20,25
Headway	5,7,10,15,20,25
Number of Possible Routes	5
Available Bus Type Cases	43 passenger, 14 and 43 passenger

❑ ***Evaluation Using ASPIRES***

- Using the optimized routes from the 2,268 model runs we were able to construct a weeklong schedule of routes for each combination of maximum in-vehicle travel time, headway, arrivals standard deviation, and available bus types. This led to 108 distinct weeklong schedules of optimized bus routes.
- The 108 weeklong schedules were simulated in a stochastic environment using ASPIRES for four consecutive weeks.

❑ ***Baseline Case***

- To provide a point of comparison a baseline simulation was constructed to create the most accurate representation of current bus operations using the data sources mentioned and information from conversations with bus operations staff at DFW.



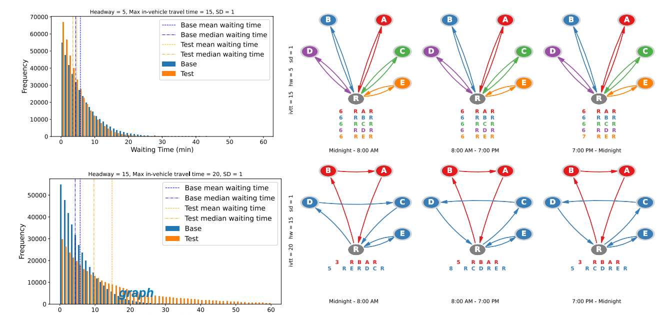
RESULTS

❑ ***Baseline Simulation Statistics***

- 11895 GGE used on average per week, average waiting time of 5.7 minutes for a bus.

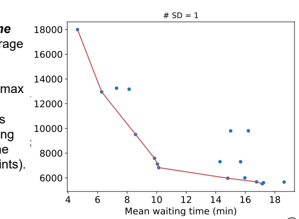
❑ ***Optimized Routes Examples***

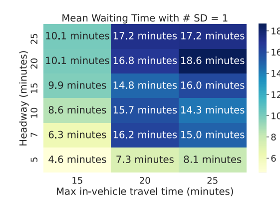
- In the first example below max in-vehicle travel time and bus headway are chosen to be very stringent. We see the optimal routes are the most direct routes between terminals and the rental car center. Additionally, we see high numbers of buses on each route throughout the day. Finally, we see the the distribution of passenger waiting times is very close to the baseline case. We note that in this case the average waiting time for a bus is 4.6 minute and on average uses 51% more GGE per week than our baseline simulation.
- In the second example below the max in-vehicle travel time and bus headways were less stringent. As a result, less buses were used on the routes throughout the day, and the optimal routes visited multiple terminals before returning the rental car center. The histogram of passenger waiting times has a larger tail than the baseline case, and the average waiting time for a bus is 14.8 minutes. These routes use 50% less GGEs on average per week then our baseline simulation.

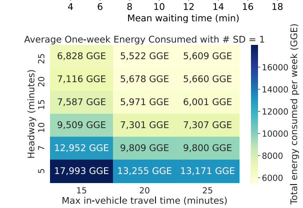


❑ ***Energy Consumption vs. Passenger Waiting Time***

- The two heat maps below illustrate how the average GGEs used per week and the average time a passenger waits for a bus are changed by using routes optimized against different headway and max in-vehicle travel time parameters.
- To show the trade-off present between the GGEs used per week and the average passenger waiting time we have plotted these quantities against one another for each hw and ivtt combination (18 points). We have also drawn the trade-off frontier in red.







CONCLUSION

❑ ***Insights Gained***

- Simulation of routes in a stochastic environment proved to be a useful way to understand the trade-offs between energy consumption and passenger waiting times.
- Reducing fleet energy consumption, and passenger waiting time are competing objectives, where a trade-off frontier is present.
- Route combinations exist where average weekly energy consumption is reduced by 20-25% while only increasing the average waiting time for a bus from 5.7 minutes to 7.7 minutes.
- Route combinations where the average waiting time for a bus was reduced below the baseline value of 5.7 minutes all resulted in at least a 50% increase in energy consumption.
- Even without changing routes there are opportunities at DFW to reduce energy consumption by 20% by taking a data driven approach to assigning the number of buses to routes depending on the demand for a given time of the week.

❑ ***Key References***

1. Kotz A, Ficenec K, Kelly K, Berger S. Electrification of Airport Shuttle Operations. InProceedings of the 33rd Electric Vehicle Symposium 2020 Sep 13.
2. https://github.com/NREL/ATHENA-bus
3. https://github.com/NREL/ATHENA-aspires

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